Corchado, J. M., et al. (Eds.) (2014). *17th International Conference on Information Fusion (FUSION 2014): Salamanca, Spain 7-10 July 2014*. IEEE.

# Navigation capabilities of mid-cost GNSS/INS vs. smartphone

## Analysis and Comparison in Urban Navigation scenarios

Enrique Martí, Jesús García, José M. Molina
Group of Applied Artificial Intelligence
Computer Science, UC3M
Colmenarejo, Spain
{emarti, jgherrer}@inf.uc3m.es, molina@ia.uc3m.es

***Abstract*—High accuracy navigation usually require expensive sensors and/or its careful integration into a complex and finely tuned system. Smartphones pack a high number of sensors in a portable format, becoming a source of low-quality information with a high heterogeneity and redundancy.**

**This work compares pure GNSS/INS capabilities on both types of platform, and discuss the weaknesses/opportunities offered by the smartphone. The analysis is carried out in a modular context-aware sensor fusion architecture developed for a previous work. It intends to serve as a preparation for answering bigger questions: can smartphones provide robust and high-quality navigation in vehicles? In which conditions? Where are the limits in the different navigation scenarios?**

***Keywords—smartphone; low-cost; navigation; context; sensor fusion***

## I. Introduction

For over a decade, GNSS/INS systems have been a common choice for supporting navigation in ground vehicles, or as part of the development of Intelligent Transportation Systems (ITS).

We are getting close to a decade of wide smartphone spreading. In that time, they have become devices with astonishing sensing capabilities including GPS positioning, inertial sensors, atmospheric pressure (barometer), magnetic field (magnetometer), temperature, light, proximity, sound (microphones) and high definition video cameras. They are within reachable limits even for personal budgets: in fact about one fifth of world population owns a smartphone, while in developed countries the share is around 70%.

Thanks to their availability and features, smartphones as sensing platforms are good tools for automatizing some tasks or assist humans performing them. A major problem is that the sensors mounted in a smartphone are required to be very small, light, cheap and power-conservative. This fact limits their features and overall quality.

An example of this limitation can be found in inertial sensors: accelerometers and gyroscopes are both triaxial MEMS-type (MicroElectroMechanical Systems), characterized by a high bias with a low stability over time. The resulting consumer-grade

In many cases, the quality gap with respect to traditional sensors will difficult or even prevent translating previous algorithms and getting similar results. However, the high number of sensors and the existing redundancy (e.g. apart from GPS-calculated altitude, the barometer can provide an invaluable help for calculating relative changes on that magnitude).

This work presents a data quality comparative analysis between a smartphone and a specialized solution that is roughly ten times more expensive, not easily portable, and requires custom made software.

Part of the conclusions are based on quantifiable indicators of raw data. The rest of them have been extracted from the result of applying a sensor fusion process to the datasets. The software in charge of performing the fusion is designed to be generic, and thus not specialized or specifically tuned for the features of any set of sensors.

The goal is to check if the sensing capabilities of a modern smartphone are enough to approach the problem of GNSS/INS navigation in urban scenarios.

## II. On GNSS/INS integration for navigation

Autonomous driving solely based on GNSS/INS sensors has been successfully implemented in some scenarios as automated agriculture. Nowadays, major manufacturers of tractors and agriculture vehicles include driverless machinery on their catalogue. However, this is possible due to the very special characteristics of that scenario: open spaces (GNSS signal is always available), restricted locations without dynamic elements, low speeds and no obstacles.

But building an autonomous driving system for open roads with real traffic is a more complicated task. Although GNSS/INS sensors are a fundamental part of navigation systems [1][2], the most successful projects (as Google Self-driving Car, or the winners of the former DARPA Challenge [3]) usually integrate them just for rough location and pose estimation. There are three fundamental reasons that discourage using this combination for navigation purposes:

- GNSS receivers are subject to large blackout periods (e.g. tunnels or underground parking lots).

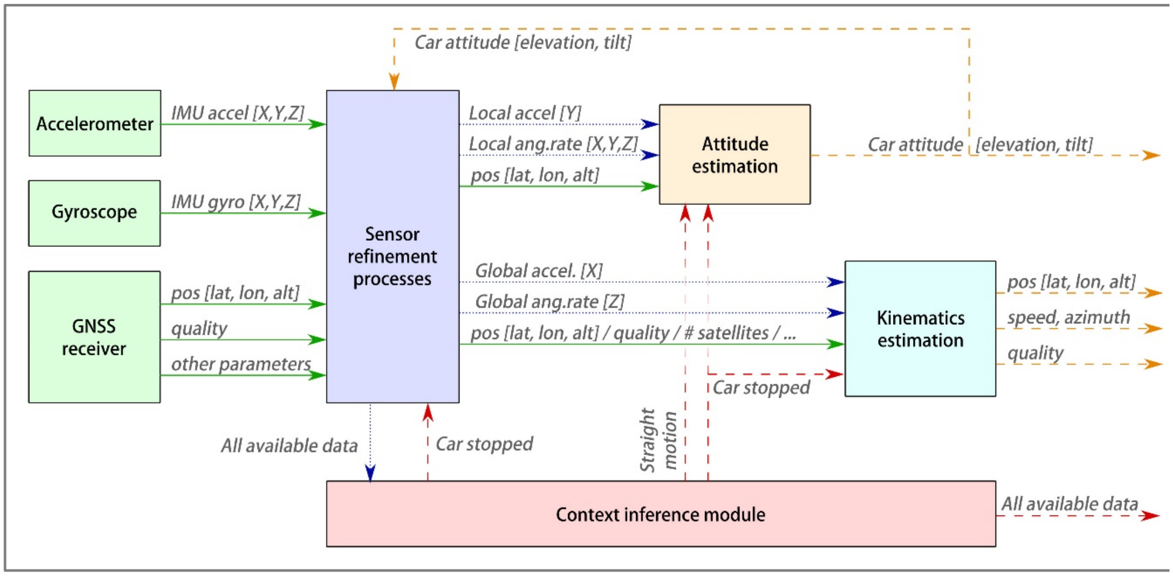


Fig. 1. Proposed sensor fusion architecture, particularized to navigation problem

- Dead-reckoning navigation for medium to long periods of time require military/strategic grade inertial sensors, which are expensive and bulk. Even in that case, the error without GNSS positions will grow unbounded over time. A solution with these features is explored in [4], offering an accumulated error within 20 meters after 5 minutes. The setup cost is around $30k
- These sensors provide no information about the environment: road, obstacles, or other vehicles.

The aforementioned projects rely instead in a combination of visual and laser sensors. Apart from the high accuracy of advanced techniques such as visual odometry or three-dimensional map matching, they can detect other agents as pedestrians and vehicles. This is a fundamental feature in a highly dynamic environment. The main disadvantage of the existing systems is the cost: as an example, Google Self-driving Car is equipped with $150k worth in sensors.

The interest in GNSS/INS extends over the development of automated driving system. An example is driver assistance, as in the case of GPS navigators. The position calculated by low cost consumer devices is fused with road map information, for a final solution that is enough in most cases.

But the use of GNSS devices in urban scenarios pose a challenge known as “urban canyon” [REF], where buildings and other elements can occlude the satellites or reflect their signals, introducing a large error in the calculated location. Under these conditions, even map fusion strategy can fail. Some of the proposed solutions work directly with the raw GNSS solution using environment models that take into account occlusions [5], or by detecting/correcting multipath effects [6], [7].

This problem is an opportunity for GNSS/INS fusion schemes with low-medium cost sensors and a certain degree of redundancy. A brief review of existing literature reveals the interest of scientific community on the potential of these devices, when applied to ground vehicle navigation [8] [9] [10].

In a very recent work [11], vehicle speed is calculated with an error of 1-3 km/h using only inertial measures. This demonstrates how a wise use of contextual knowledge can be used to infer very useful navigation information even from low-end sensors.

This work is a preliminary analysis on the possibilities of a sensor fusion system that can work with heterogeneous data sources including smartphones, where the different sources can be unavailable. Exploitation of domain-specific information is expected to be a fundamental part of the system, so that the experiments will test the performance of the proposed tool with different sources and conditions.

## III. Fusion Architecture

In the introduction we have defined some desirable properties for a sensor fusion software solving our problem. Pure performance is secondary, in favor of:

- Low dependency on input data features: sensor and data sources can change their presence and features (quality, accuracy rate) dynamically.
- Adaptability: the system should be able to monitor its integrity and performance, in order to react and offer the optimal output
- Modularity: previous features encourage a design based on individual modules interconnected. They should have a purpose themselves (generate a meaningful output), and be as independent from the rest as possible.

The experiments described on this paper use a piece of software developed in a previous work [12]. This software implements a loosely coupled fusion architecture (shown in Fig. 1) that tries to match the aforementioned characteristics. It relies on detecting external conditions (context) that modify the

This work was supported in part by Projects MINECO TEC2012-37832-C02-01, CICYT TEC2011-28626-C02-02, CAM CONTEXTS (S2009/TIC-1485).

processing scheme or trigger automatic diagnosis and calibration routines.

This scheme was successfully applied to a mid-cost sensor set in the former work, and is tested here with data gathered by a smartphone.

### A. Novatel GPS

The mid-cost GNSS solution is a Novatel OEMV-1G board. It offers GPS+GLONASS L1 tracking, providing reliable positioning even in obstructed sky conditions. The receiver is embedded on a Novatel compact enclosure (FlexPak-G2-V1G) for outdoor applications as base station and vehicle position in urban environment.

This device can work in differential mode (DGPS), although it is set in single point position mode (SINGLE mode) for the experiments of this paper. The “optimal conditions” term in SINGLE mode refers to observing six or more healthy satellites and relatively low multi-path (to assure enough quality of the received data).

### B. MicroStrain IMU

We have selected a MicroStrain 3DM-GX2 IMU, which integrates triaxial accelerometer, gyroscope and magnetometer. It is a high-quality MEMS-based device in the price range of the few thousand dollars, so it is considered a low-cost device by some studies [13].

It includes an internal Complementary Filter [REF] that fuses raw data into a stabilized attitude estimation. The accuracy of the calculated orientation is around 0.5-2.0º according to manufacturer specifications.

The proposed experiments focus on raw gyro and acceleration data instead, since they are more suitable for calculating the required pieces of contextual knowledge.

### C. Smartphone

Experiments are based on the data captured by an LG Nexus 5 smartphone. This high-end terminal features the following sensors:

- Accelerometer+Gyroscope InvenSense® MPU-6500™. This chipset produces raw measures, as well as some processed outputs such as attitude or step count (podometer).
- Magnetometer AsahiKasei AK8963
- Barometer Bosch Sensortec BMP280. Provides altitude with a relative accuracy equivalent to +-1 m, and a temperature offset equivalent to 0.12m/K.
- GPS is integrated in the RF processor, Qualcomm WTR1605L (2G+3G+4G-LTE+GPS). Apparently, these chipsets integrate some limited WAAS/EGNOS functionality, improving horizontal location accuracy up to 3m (1 sigma) in optimal conditions. This statement is not confirmed by the documentation available on manufacturer website.

Data is captured using a custom Java (Android) application. Sensors are accessed through Android API, abstracting the real hardware and its details. The application sets sensors to provide the highest possible update rate. TABLE I. describes the compared refresh rates of the employed devices.

TABLE I. SENSOR REFRESH RATE

| | Refresh rate | |
|---|---|---|
| **IMU** | ***Maximum*** | ***Configured*** |
| MicroStrain | 300 Hz | 50 Hz |
| Smartphone | 100 Hz (estimated) | 50 Hz |
| **Magnetometer** | ***Maximum*** | ***Configured*** |
| MicroStrain | 300 Hz | 50 Hz |
| Smartphone | 100 Hz (estimated) | 50 Hz |
| **GPS** | ***Maximum*** | ***Configured*** |
| Novatel | 10 Hz | 1 Hz |
| Smartphone | 1 Hz (varies) | As fast as possible |
| **Barometer** | ***Maximum*** | ***Configured*** |
| Smartphone | 1 Hz (estimated) | As fast as possible |

## IV. RESULTS

The presented results are based on a single open traffic experiment, which was recorded simultaneously by the mid-cost system and the smartphone. We drove the test vehicle in the surroundings of Leganés Campus (Universidad Carlos III de Madrid), describing the 4.5km long trajectory shown in Fig. 1 in around 1100 seconds. Slope is in the range [-5%; 6%], with average value 1.7% (based on public altimetry maps).

Slope is an important feature that affects how accelerometer data must be interpreted. If this data is integrated to estimate vehicle speed, a poorly calculated slope can introduce large errors.

This trajectory features a typical urban driving scenario in Spain: buildings around five floors high, narrow streets, roundabouts, different types of pavement (including bumps), and regular speed/stop patterns.

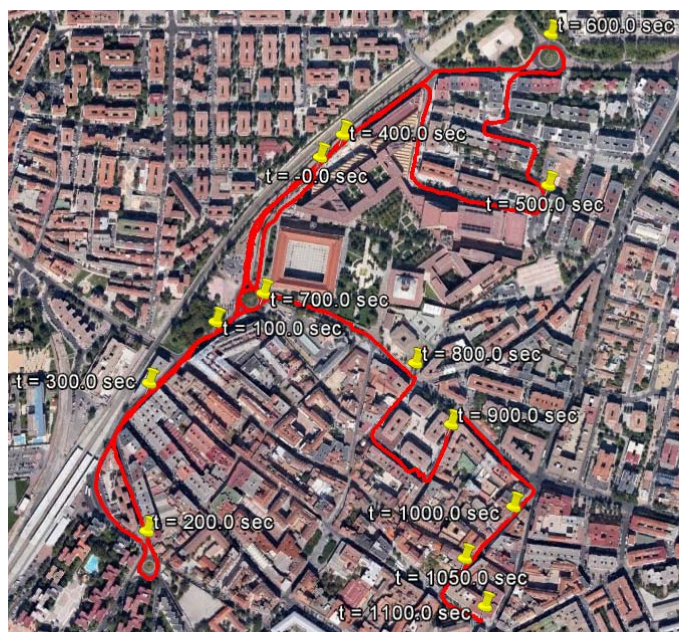


Fig. 1. Trajectory followed by the test car. The presented results are based on this record.

## A. GPS quality

Before reviewing the quality of GPS devices, let us remark that the trace recorded by Novatel GPS is quite atypical. The device was subject to blackouts between 5 and 50 seconds long in relatively open places. It also triggered several alarms revealing problems in the calculated solution (integrity warnings and singularity in covariance matrix among others). This was probably caused by start recording data a short time after a cold start. However, we opted to keep it since it proposes very interesting situations for further experiments.

As a rule of thumb, Novatel GPS fixes have a far superior quality compared with the smartphone. The principal factor is most probably the antenna: satellite signal reception is much clearer.

The consequences can be observed in the number of satellites detected by each device (Fig. 2.), and also the number of satellites used by Novatel device when determining the last fix. In spite that the constellation of the smartphone is reduced (never above 10 satellites), it is much more constant: between 400 and 750 seconds, it never goes down 7 satellites. On the other hand, Novatel device oscillates between 5 and 16 visible satellites.

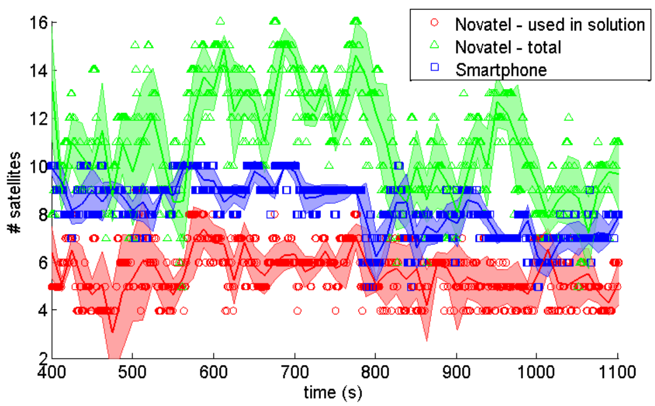


Fig. 2. Number of satellites over time

The superior quality of Novatel fixes is illustrated in Fig. 3. It shows a piece of the trajectory, as recorded by both sensors. It has been selected to be representative of remarkable effects found in the full sample. Observation conditions are good: open sky, no severe multipath problems. The vehicle enters the left part of the image, on the right (bottom) lane of the street, and then turns right on the junction to disappear on the bottom. Later on, the car reappears on the top-right side of the image, and drives back to the point where it first entered into scene.

The green trajectory corresponds to the date recorded by Novatel GPS device. It is possible to discern on which lane the car is driving; maneuvers are clearly, accurately depicted. This is characteristic of a system with a very low relative error.

The red line represents smartphone trace. Both relative and absolute errors are higher (unable to discern lanes, since the two lines do cross several times), and maneuvers show some "inertia", that is likely to be caused by internal processing on the device –on-chip assisted GPS algorithms, operating system corrections such as fusion/filtering/smoothing.

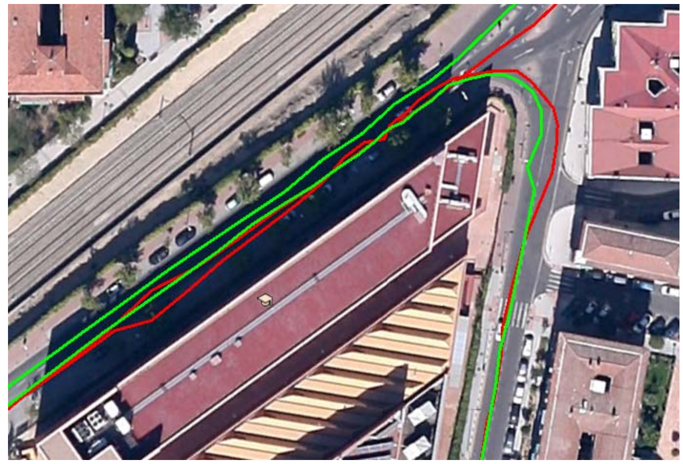

Fig. 3. Comparison of Novatel GPS (green) and smartphone (red) raw fixes. Detail

Establishing a comparison for both accuracies is a complex task, because we lack groundtruth data. An alternative solution is to align both series of GPS fixes to a common timeline and compare their discrepancies with the accuracy information provided by the sensors.

Data is aligned by applying linear interpolation between consecutive fixes. The result for part of the experiment is shown in Fig. 4 (the line for distance between fixes has been smoothed for a clear visualization).

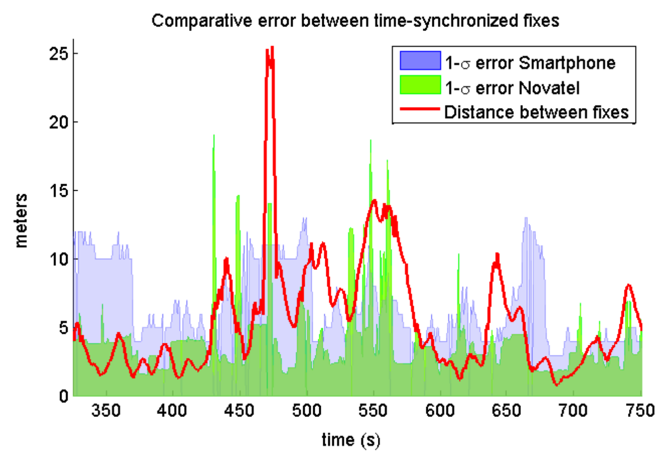


Fig. 4. Distance between GPS fixes from Smartphone/Novatel devices, compared with the self-reported accuracy (one standard deviation)

The difference between both GPS traces follows a segmented pattern. When satellite visibility conditions are good, this difference is around a single standard deviation of the best sensor (before t=420 s in the figure). The highest peaks are concentrated between t=420 and t=550, matching those Novatel fixes with the largest reported errors, that also happen to have a large bias. We find reasonable to conclude that this puntual errors in the mid-cost GPS system are the main cause of the error peaks in the plot.

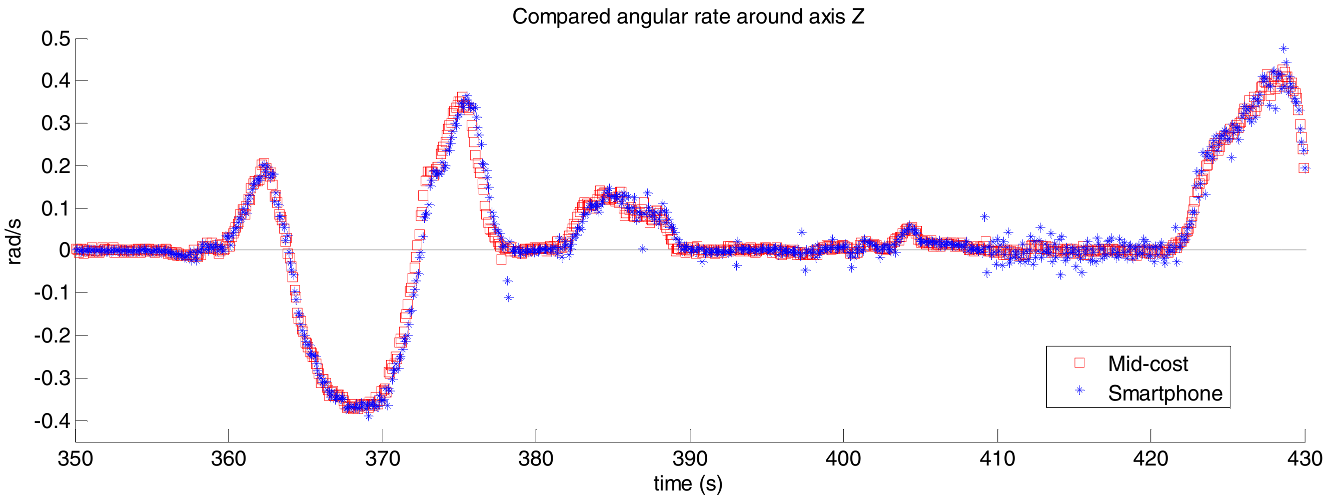


Fig. 2. Compared angular rate on mid-cost and smartphone gyroscope (subsampled for the sake of clarity). The comparison exposes anomalies, as the smartphone signal becoming noisier around t=410s, or a 0.3 seconds delay from t=370s to the next straight fragment, around t=390s

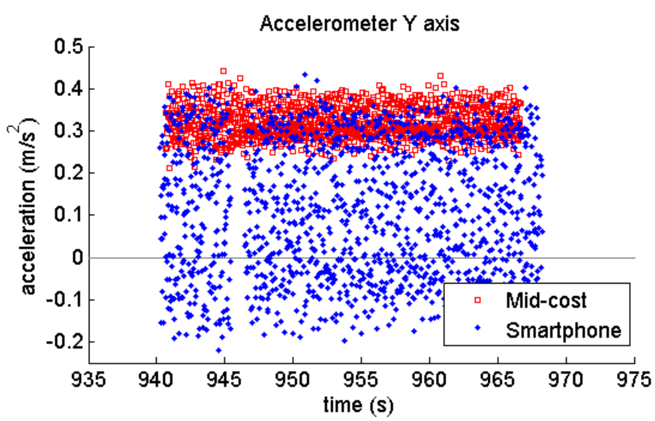


Fig. 5. Accelerometer readings with the vehicle stopped. Note that bias is not corrected on these samples.

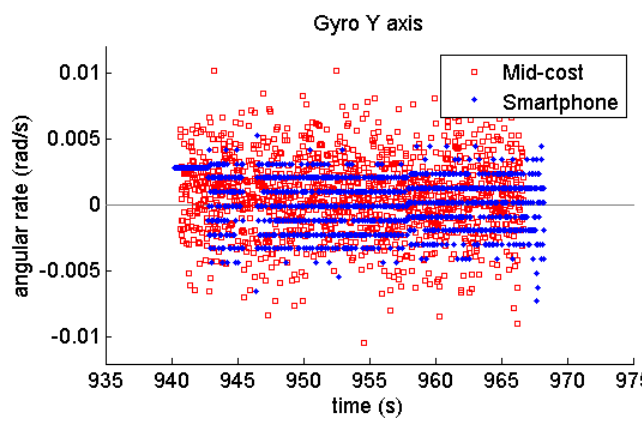


Fig. 6. Gyroscope readings with the vehicle stopped

### *B. Inertial measures quality*

A comparative sample of accelerometer data along Y axis is shown in Fig. 5. It was taken with the vehicle stopped, and illustrates the accuracy of each sensor. The calculated standard deviation calculated for MicroStrain mid-cost device is four times lower than smartphone readings.

Gyroscope readings around the same axis, for the same period of time, are shown in Fig. 6. Smartphone gyro shows a strong quantization effect, but its standard deviation is surprisingly lower than that of mid-cost gyro. The quantization step (0.06 deg/s) is consistent with the 16 bit AD converter working over a scale of 2000 deg/s. Setting smartphone gyro on a lower scale (more suitable for vehicle navigation) would improve these results. However, Android sensor manager documentation indicates that gyro maximum range must be at least 1000 deg/s, and it does not expose any method that can modify the setting. Changing the range is probably not compatible with normal smartphone functioning.

TABLE II. describes the noise of each sensor during stops, as extracted from experimental data.

TABLE II. NOISE LEVELS OF IMU COMPONENTS

| **Accelerometer** | **Std. deviation** |
|---|---|
| MicroStrain | 0.038 $m/s^2$ |
| Smartphone | 0.159 $m/s^2$ |
| **Gyroscope** | **Std. deviation** |
| MicroStrain | 0.171 deg/s |
| Smartphone | 0.118 deg/s |

Fig. 2 tries to gather in a single plot all the strange effects found in smartphone inertial data. In first place, it is common that during maneuvers, as the one taking place between t=360 and t=380 seconds (a roundabout), smartphone reading is temporarily delayed about 0.3 seconds. The delay starts at t=370s and extends for 20 seconds.

Later, at t=410 seconds, smartphone gyro output becomes noisier for about a minute (standard deviation up to five times higher). This happens in the three axes, and returns later to normal levels. The best explanations for this behavior is that, while the mid-cost IMU is attached to the body of the car, the smartphone lies free on a surface. Driving dynamics can affect how firmly the smartphone rests on that surface, and this is translated into different vibration levels.

### C. *Automatic context extraction*

Simple automated techniques can achieve comparable results for both sets of data. The best candidate is an algorithm that:

- Does not have a strong dependence on the quality of the sensor.
- Does not require prior calibration
- Is robust under sensor dynamic changes (e.g. bias drift, temperature offset)

An example is the algorithm for detecting vehicle stops. It works over accelerometer data, split in chunks. The amplitude of each chunk (difference between maximum and minimum value) is consistently low when the car is stopped, so that detection by means of thresholding is possible. This algorithm is independent of the orientation of the sensor (even in a smartphone that can change its position during the record), and works over biased data. The threshold can be estimated automatically using only inertial data using simple statistics. As a side note, chunk amplitude criterion is more consistent and clear than using the standard deviation of the signal, as used in [11].

Below, Fig. 7 and Fig. 8 show relevant pieces of the detected stops and straight fragments, after applying the same non-parameterized algorithms to both sets of data (mid-cost equipment and smartphone).

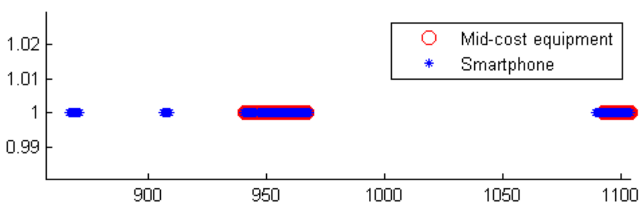


Fig. 7. Sample of stop detection output, compared for both sensors

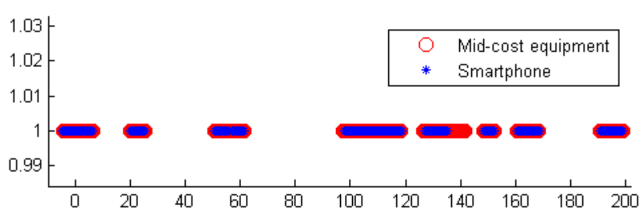


Fig. 8. Sample of straight motion detection output, compared for both sensors

Results are comparable. In spite that the smartphone output is a bit more sensitive in the case of stop detection, it allows to estimate the gyroscope bias with similar accuracy. The proof is that the output of straight motion detection algorithm, that requires unbiased gyro measures, is very similar for both sensors: the figure shows the only discrepancy found in the whole trajectory, around t=140s.

### D. *Navigation capabilities*

Lacking groundtruth data, the first conclusion is that the general navigation accuracy is more or less similar for both platforms. The lower accuracy of the smartphone is balanced with a smoother output and reduced blackout time.

More interesting is comparing the performance of three dimensional attitude estimation. Our algorithm is based on two separate Unscented Kalman Filters (UKF) that combine IMU input with corrective updates based on GPS fixes, and some information inferred on special events (stops, turns).

The inferred pitch angle is quite similar for both devices when GPS availability is good. When the vehicle enters the urban canyon, pitch angle estimation is suddenly altered. The effect on both sets of sensors is different, although the result is similarly devastating for dead-reckoning purposes. However, attitude estimation is better for the mid-cost solution: pitch angle never goes above (or below) ±5 degrees, while smartphone estimation reaches ±8 degrees sometimes. The ideal value should be within ±3 degrees (equivalent to a 5% slope).

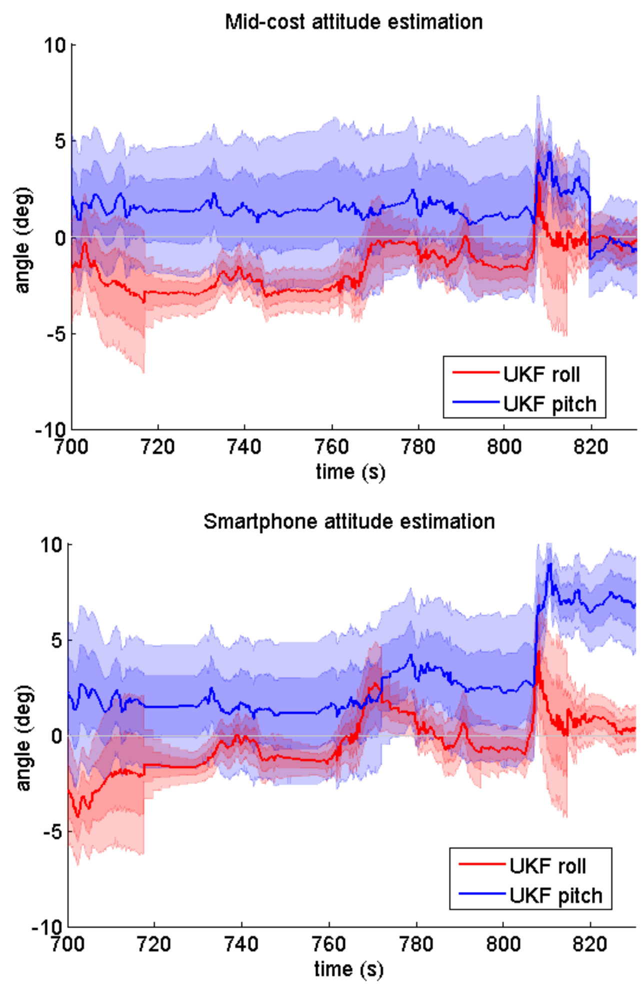


Fig. 9. Sample of attitude estimation (pitch/roll angles) as calculated from mid-cost equipment and smartphone. It combines zones with good satellite visibility before t=780, and degraded GNSS performance in advance.

Roll angle estimation has a constant bias of about two degrees in the smartphone, probably caused by its placement in the car.

We conclude that the obtained results are good. Our initial expectations were lower, taking into account all the handicaps of the smartphone system: lower sensor quality, not attached to the body of the car, lack of prior calibration, and standard software that has not been designed for it, nor tuned to match its exact features.

On the other hand, the obtained accuracy levels are not enough under degraded GNSS performance. It would be desirable to integrate other sensors such as barometer and magnetometer. We expect huge benefits from exploiting those two sensors for attitude estimation.

## V. CONCLUSIONS

This paper compares the INS/GNSS data as recorded with a mid-cost system and a smartphone. This information is processed using a sensor fusion system for ground vehicle navigation, which can infer pieces of information that are used for self-calibration and navigation quality improvement.

Results show fundamental differences in the sensed data between the mid-cost equipment and a smartphone. Apart from a negative qualitative gap, the data provided by smartphones is less controllable and sometimes appears to be pre-processed – presents features as smoothing, latency or inertia.

The detected differences have a direct impact on the accuracy of traditional navigation algorithms. On the other hand, our software is able to extract contextual information with similar results for both sets of sensors. As a future work, we want to analyze new uses of contextual data to feedback the fusion process –algorithms, architecture, parameters.

A real time application would require further developments, including online estimation of smartphone pose with respect to vehicle axes (this has been analyzed in [14]), optional integration of car onboard sensors as OMBD-II chip, and detect if smartphone data is not reliable (e.g. a person is holding it on its hand)

## ACKNOWLEDGMENT

Authors want to thank Dr. David Martín for its invaluable help and patient work. Setting up the experiments would have been an ordeal without his experience and support.

## REFERENCES

[1] D. M. Bevly and S. Cobb, *GNSS for Vehicle Control*. Artech House, 2010, p. 284.

[2] P. D. Groves, *Principles of GNSS, inertial, and multi-sensor integrated navigation systems*. Artech House, 2008, p. 518.

[3] M. M. H. D. D. S. A. A. J. D. P. F. J. G. M. H. K. L. C. O. M. P. V. P. P. S. S. S. C. D. L. J. C. K. Sebastian Thrun, “The Robot that Won the DARPA Grand Challenge.”

[4] R. E. Mandapat, “Development and Evaluation of Positioning Systems for Autonomous Vehicle Navigation,” University of Florida, 2001.

[5] B. Ben-Moshe, E. Elkin, H. Levi, and A. Weissman, “Improving Accuracy of GNSS Devices in Urban Canyons.”

[6] E. Falletti and N. Linty, “Evaluation of the multipath-induced error probability on the estimation of code-based pseudoranges,” in *2012 6th ESA Workshop on Satellite Navigation Technologies (Navitec 2012) & European Workshop on GNSS Signals and Signal Processing*, 2012, pp. 1–8.

[7] P. Axelrad, C. J. Comp, and P. F. Macdoran, “SNR-based multipath error correction for GPS differential phase,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 32, no. 2, pp. 650–660, Apr. 1996.

[8] J. Wallin and J. Zachrisson, “Sensor Fusion in Smartphones: with Application to Car Racing Performance Analysis,” Linköping University, 2013.

[9] N. Magnusson and T. Odenman, “Improving absolute position estimates of an automotive vehicle using GPS in sensor fusion,” Chalmers University of Technology, 2012.

[10] O. Walter, J. Schmalenstroeer, A. Engler, and R. Haeb-Umbach, “Smartphone-based sensor fusion for improved vehicular navigation,” in *2013 10th Workshop on Positioning, Navigation and Communication (WPNC)*, 2013, pp. 1–6.

[11] H. Han, J. Yu, H. Zhu, Y. Chen, J. Yang, Y. Zhu, G. Xue, and M. Li, “SenSpeed: Sensing Driving Conditions to Estimate Vehicle Speed in Urban Environments,” in *Proceedings of the IEEE International Conference on Computer Communications*, 2014.

[12] E. D. Martí, D. Martín, J. García, A. de la Escalera, J. M. Molina, and J. M. Armingol, “Context-aided sensor fusion for enhanced urban navigation.,” *Sensors (Basel).*, vol. 12, no. 12, pp. 16802–37, Jan. 2012.

[13] H. Chao, C. Coopmans, L. Di, and Y. Chen, “A comparative evaluation of low-cost IMUs for unmanned autonomous systems,” in *2010 IEEE Conference on Multisensor Fusion and Integration*, 2010, pp. 211–216.

[14] J. Almazan, L. M. Bergasa, J. J. Yebes, R. Barea, and R. Arroyo, “Full auto-calibration of a smartphone on board a vehicle using IMU and GPS embedded sensors,” in *2013 IEEE Intelligent Vehicles Symposium (IV)*, 2013, pp. 1374–1380.